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Design and Implementation of MPC for Energy Optimization of Boiler in Batch Distillation Column

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***Abstract*— A competency in the industrial world depends on several aspects, that is cost, delivery, flexibility, and quality. The smart industrial system / Smart Manufacturing System (SMS) tries to improve those aspects using the latest technology that encourages the use of digital information widely and quickly in industrial systems. Development of SM in industry 4.0, pushing the change of industrial pyramids into Cyber-Physical System (CPS). CPS has begun to be applied widely in process industries nowadays, i.e., distillation process industry. In distillation process, boiler has the important role to separate 2 different components using the difference of its boiling point. In this paper, the alcohol distillation plant is used to purify 30% of alcohol solution. The modelling of boiler, simulation, and implementation of boiler control system are presented to get the desired temperature. The temperature reference is roughly 85 °C. Predictive Model Controller (MPC) and Kalman Filter is proposed to control the temperature of boiler by adjusting the PWM of on-off time and to deal with the disturbance and sensor noise. The IAE, ISE, and ITAE is analyzed to obtain the error of control system and energy usage per operation is also calculated to find out the effect of MPC controller in energy optimization.**

Keywords—CPS, Batch Distillation Column, Model Predictive Control, Energy Optimization, Kalman Filter.

I. INTRODUCTION

The fourth industrial revolution, also called industry 4.0, has encouraged the connectivity between object in industry through Cloud, Big Data Analytics, and Internet of Things (IoT). The main idea of industry 4.0 is to utilize these technologies and concepts such as:

1. Availability and the use of internet and IoT.
2. Integration of technical process and business process.
3. Digital mapping and virtualization of the real world.
4. Smart factory.

Pyramid industrial is the core of smart factory ecosystem which product cycle, production cycle, and business cycle converge and interact each other. Pyramid industrial can be represented in 4 levels, that is device level, SCADA level, Manufacturing Operation Management (MOM) level, and Enterprise Resource Planning (ERP) level [1].

CPS nowadays has been applied to various type of industries, one of which is the distillation process industry. The process of separation in distillation is carried out in different temperature, pressure, composition, and/or state phase [2]. In distillation process, the lighter component (more volatile) will be concentrated in vapor phase and the heavy component (less volatile) will be concentrated in liquid phase. The relationship between vapor phase and liquid phase is represented in Vapor-Liquid Equilibrium relation for various components. The main purpose in controlling distillation column is to maintain the desired component on top product and bottom product. The top product composition is maintained by controlling the reflux ratio and the bottom product composition is maintained by controlling boil-up rate [3]. In [4] and [5], boiler is controlled by adjusting steam flow through valve. In this paper, boiler temperature is controlled by adjusting on-off time PWM so that the desired boiling point is obtained.

Several researches on distillation column system are proposed. In Wahid and Putra [6], 3 control schemes are used to control stage temperature in rectifying and stripping section of reactive distillation column for Dimethyl Ether production, that are Multivariable Model Predictive Control (MPC), two-point PI control, and single-point PI control. In Biyanto et.al [7], artificial Neural Network is proposed for modelling and controlling the distillation column system. The control strategy being used is Neural Network Internal Model Control (NN-IMC) using forward and inverse model based on Neural Network (NN). In other research, modelling and PI control on boiler of distillation column are proposed by Mario et.al [8]. Boiler being used is electric boiler which its model is consisted AC-DC converter, DC-DC buck converter, and a PI voltage controller.

In process industry, distillation process has 25-40% energy consumption [9]. The process of distillation column in transforming the liquid phase to vapor phase and back again to liquid phase consumes a lot of energy and boiler is one of it. Therefore, the temperature of boiler affect the energy efficiency in distillation column. In Lanny Robbins et al [10], the temperature control by adjusting steam flow rate using several methods is suggested.

In this paper, control design of alcohol distillation column boiler is proposed by implementing Model Predictive Control (MPC). The main purpose of controlling boiler system is to maintain the boiler at its operational temperature or it is called regulatory and to optimize energy usage of boiler. Boiler system on distillation column has high nonlinearity property. This nonlinearity property is caused by a saturation temperature in atmospheric pressure of 1 atm and the change in mass of the mixture when the temperature is above the boiling point of solution. Therefore, to deal with this nonlinearity property, the control strategy being used is by controlling the temperature around its operational temperature, that is 85 Degree Celsius, and assuming the mass changing as a system disturbance. By assuming the mass changing as a system disturbance, so implementing Kalman Filter (KF) is proposed. Kalman Filter is not only for dealing with a system disturbance, but it is also for estimating the temperature state of boiler as a result of 3rd order of Pade approximation in compensating process time delay. Some research about state estimation of distillation column has been proposed. In Sree et.al [11], estimation of temperature for trays T3, T4, T5, and T6 is proposed to obtain purity of the top product and bottom product. In Simon et.al [12], it is shown that estimation of composition, liquid level, and pressure in various stages can be done using Extended

Kalman Filter (EKF). In other research, Ali et.al [13] proposed On-line Nonlinear Dynamic Data Reconciliation (NDDR) method using Extended Kalman Filter (EKF). In that research, the method is implemented for measuring the temperature of distillation column and measuring the concentration of Continuous Stirred Tank Reactor (CSTR). Contribution of this paper are:

1. To maintain operational temperature of boiler by implementing Model Predictive Control (MPC).
2. To implement 3rd order of pade approximation for process delay of boiler system.
3. To compensate system disturbance and sensor noise by implementing Kalman Filter (KF).

This paper consists of 6 sections. CPS architecture and modelling of boiler in mini batch distillation column are presented in section 2 and section 3. In section 4, control design of boiler in mini batch distillation column is discussed. The experiment result is in section 5 and then its conclusion is concluded in section 6.

II. CPS ARCHITECTURE OF BOILER IN MINI BATCH DISTILLATION COLUMN

A. *Control Architecture of Boiler*

The control loop of boiler in distillation column is shown in Pipe and Instrumentation Diagram (P&ID) on Fig. 1 below. The control strategy for boiler system is to maintain the operational temperature around 85 Degree Celsius as shown in Fig. 2 below. The manipulated variable (MV) is on-off timer of boiler or called time PWM of boiler. The controlled variable (CV) is temperature of boiler. The set point of this system is 85 Degree Celsius.

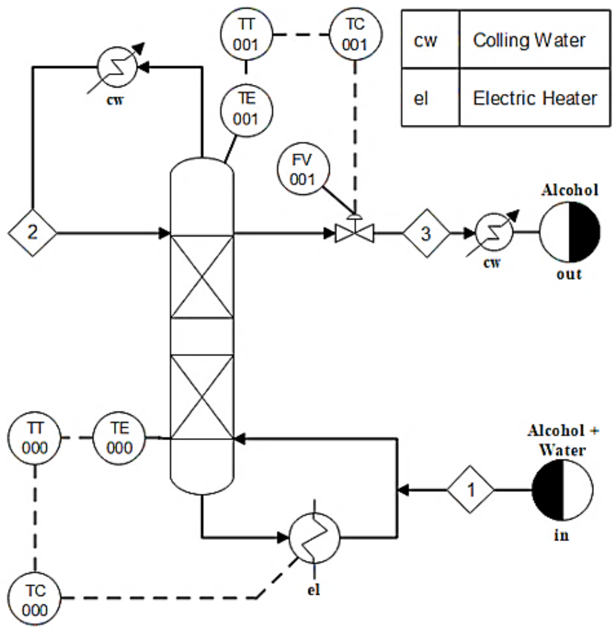

Fig. 1 P&ID of mini batch distillation column

The rhombus shape, in P&ID on Fig. 1 above, indicates the process stream of mini batch distillation column. The raw material, 30% alcohol, is filled in to boiler and at the top product, more pure composition is obtained.

Percent of Alcohol	Boiling Point	Percent of Alcohol	Boiling Point	Percent of Alcohol	Boiling Point
100	78.300	88	78.445	55	81.77
99.5	78.270	87	78.530	48	82.43
99	78.243	86	78.575	37	83.76
98.5	78.222	85	78.645	35	83.87
98	78.205	84	78.723	29	84.86
97.5	78.191	83	78.806	26	85.41
97	78.181	82	78.879	22	86.11
96.5	78.179	81	78.968	20	87.32
96	78.174	80	79.050	18	87.92
95.5	78.176	79	79.133	13	90.02
95	78.177	78	79.214	10	91.80
94.5	78.186	77	79.354	8	93.10
94	78.195	76	79.404	7	93.73
93.5	78.211	75	79.505	5.5	94.84
93	78.227	73	79.683	4.5	95.63
92.5	78.241	71	78.862	3	97.11
92	78.259	69	80.042	2	98.05
91	78.270	67	80.237	1.5	98.55
90	78.323	65	80.438	1	98.95
89	78.385	63	80.642	0.5	99.65

Fig. 2 Boiling point in various concentration of alcohol [14]

B. *NCS Architecture of Boiler*

In this research, Network Control System (NCS), that is adopted from previous research [15], is implemented to boiler system. The actuator, transmitter, and controller in device level of pyramid industrial are changed to smart actuator (SA-yy), smart transmitter (ST-xx), and smart controller (SC-zz) in NCS scheme. Complete design of NCS architecture of boiler is shown in Fig. 3 below.

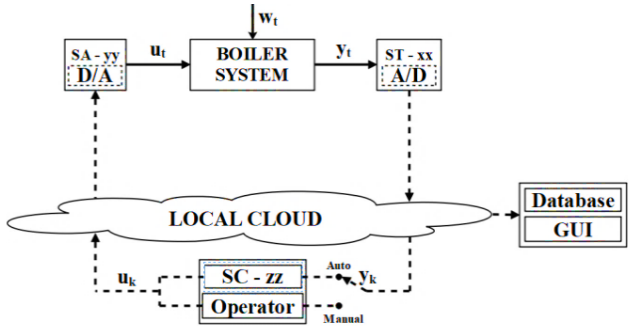

Fig. 3 NCS of boiler control system

In control scheme of NCS of boiler control system, 2 modes are implemented, that is manual mode and auto mode. If the operator/user selects auto mode, the control scheme as shown in Fig 3 will works. Otherwise, If the operator/user selects manual mode, the boiler system will work as human in the loop. The graphical user interface (GUI) is made using python library named Tkinter and SQLite library is used for database engine to create a data logger/data storage.

III. MODELLING OF BOILER IN MINI BATCH DISTILLATION COLUMN

The boiler being used is specifically refers to an electrically heated hot water system. The boiler is used to boil 3 liters of the mixture of 30% alcohol and water. The heating element, when switched on, supplies heat roughly at a constant rate of 1400 Watts. The block diagram, that illustrates the heat input and output, is shown in Fig. 4 below.

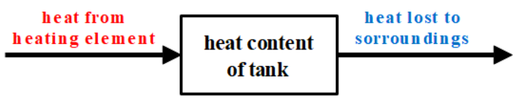

Fig. 4 Input-output block diagram for the heat content in boiler system

A heat balance for the system is described by word equation below [16],

$$\begin{Bmatrix} rate\,of \\ change \\ of\ heat \end{Bmatrix} = \begin{Bmatrix} rate\,heat \\ produced\,by \\ heating\ element \end{Bmatrix} - \begin{Bmatrix} rate\,heat \\ lost\,to \\ surroundings \end{Bmatrix} \quad (1)$$

In this research, the model is obtained by identification system of input and output boiler system. The initial condition for modelling is used 3 liters of alcohol mixture and the reflux state is off. Temperature response caused by PWM on-off timer is shown in Fig. 5 below,

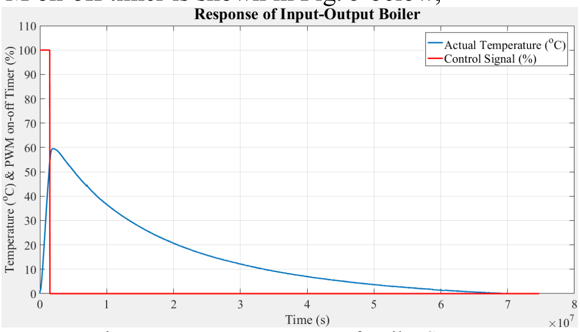

Fig 5. Temperature response of Boiler System

The data of temperature response is taken twice in same time and initial condition, first data for modelling and other for validation. Based on the data experiment of boiler temperature, the 3rd order of transfer function is obtained. Transfer function is shown in equation (2) below,

$$\frac{0.01676s^2 + 0.0001476s + 4.741*10^{-8}}{s^3 + 0.003577s^2 + 1.339*10^{-6}s + 6.509*10^{-11}}e^{-126s} \quad (2)$$

Because the output delay exists in boiler system, roughly 126 seconds, 3rd of Pade approximation is proposed to overcome output delay. Therefore, the boiler model becomes high order transfer function. The final model of boiler is shown in equation (3) below,

$$\frac{-0.01676s^5 + 0.001449s^4 - 4.933*10^{-5}s^3 + 4.521*10^{-7}s^2 + 8.675*10^{-9}s + 2.844*10^{-12}}{s^6 + 0.09882s^5 + 0.004121s^4 + 7.363*10^{-5}s^3 + 2.196*10^{-7}s^2 + 8.057*10^{-11}s + 3.905*10^{-15}} \quad (3)$$

The model validation of equation (3) is done by comparing transfer function with the actual data of boiler system. The best fit of the transfer function is 96.73%.

IV. CONTROL DESIGN OF BOILER IN MINI BATCH DISTILLATION COLUMN

A. Model Predictive Control

Model predictive control (MPC) is an optimal control method that is used to control a process by considering some constraints. The main concept of model predictive control is shown in Fig. 6.

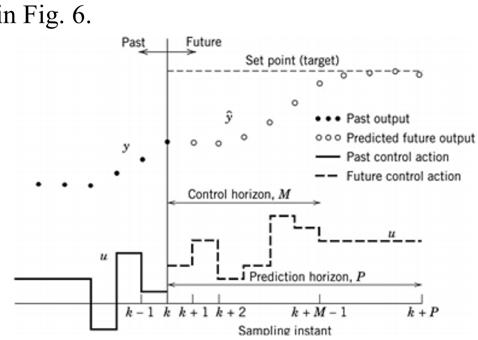

Fig. 6 Main concept of MPC

The block diagram of control strategy of model predictive control is shown in Fig. 7 below.

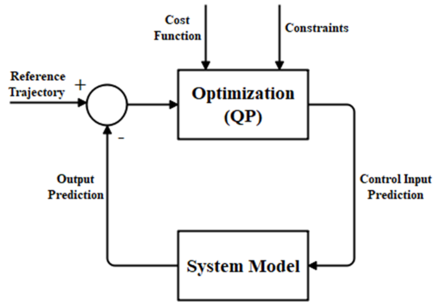

Fig.7 Block diagram of control strategy of MPC.

Quadratic programming (QP) is an optimal solution for quadratic function of several variables with existing constraints. QP problems are known as follows,

$$U = \underset{U \in U_{sat}}{\arg\min}\{J\} \quad (4)$$

With U_{sat} is the set of constraints that is defined as follows,

$$U = U_{min,i} \le U_i \le U_{max,i},\ i = 1,2,\ldots,N_u \quad (5)$$

and,

$$J = \frac{1}{2}\left(U - U_0\right)^T M \left(U - U_0\right) \quad (6)$$

To solve QP problem in equation (4), it is same as solving the Non Linear Algebraic Loop as shown in Fig. 8 below.

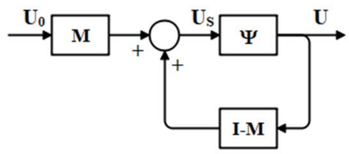

Fig. 8 Non linear algebraic loop [17].

where $\Psi_{(U_s)}$ is diagonal saturation with $\Psi_{(U_s)} := diag\left(\Psi_i(U_{s,i})\right) = U$ for $i = 1, 2, \ldots, p$.

MPC as Tracking Problem

Supposed a system is detectable and stabilizable with the following state space [17],

$$\begin{aligned} x_{k+1} &= \bar{A}x_k + \bar{B}u_k \\ y_k &= \bar{C}x_k \end{aligned} \quad (7)$$

where $x_k \in \mathbb{R}^n, y_k \in \mathbb{R}^l, u_k \in \mathbb{R}^m$ and $\bar{A}$, $\bar{B}$, $\bar{C}$ are state space form in discrete. y_k is desired to track the ω_k reference, $\omega_k \in \mathbb{R}^o$, or in the other words, the desired error tracking is $e_k = 0$. In order to tracking the reference, an integrator is used in the following form,

$$u_k = u_{k-1} + \Delta u_k \quad (8)$$

Furthermore, equation (8) is substituted to state space system in equation (7) for getting an augmented system equation as follows,

$$\begin{aligned} \bar{x}_{k+1} &= A\bar{x}_k + B\Delta u_k \\ y_k &= C\bar{x}_k \end{aligned} \quad (9)$$

where $A = \begin{bmatrix} \bar{A} & \bar{B} \\ 0 & I_m \end{bmatrix}$, $B = \begin{bmatrix} \bar{B} \\ I_m \end{bmatrix}$, $C = \begin{bmatrix} \bar{C} & 0 \end{bmatrix}$ and $\bar{x}_{k+1} = \begin{bmatrix} x_{k+1} \\ u_k \end{bmatrix}$.

If the state and output system are predicted in prediction horizon (N_p) and control horizon (N_c), the plant system will be obtained up to N_p − horizon as follows,

$$\bar{X} = \pi\bar{x}_k + \gamma U_d$$
$$Y = \phi\bar{x}_k + \Gamma U_d \tag{10}$$

with,

$$\bar{X} = \begin{bmatrix} \bar{x}_{k+1} \\ \bar{x}_{k+2} \\ \vdots \\ \bar{x}_{k+N_p} \end{bmatrix}, U_d = \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+N_c-1} \end{bmatrix}, Y = \begin{bmatrix} y_{k+1} \\ y_{k+2} \\ \vdots \\ y_{k+N_p} \end{bmatrix}$$

$\pi, \gamma, \emptyset$ and Γ are the function of matrix A, B, C.

$$\pi = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^{N_p} \end{bmatrix} \tag{11}$$

$$\gamma = \begin{bmatrix} B & \cdots & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N_p-1}B & A^{N_p-2}B & \cdots & A^{N_p-N_c}B \end{bmatrix} \tag{12}$$

$$\phi = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{N_p} \end{bmatrix} = \begin{bmatrix} \overline{CA} & \overline{CB} \\ \overline{CA}^2 & \bar{C}\left(\bar{A} + I_m\right)\bar{B} \\ \vdots & \vdots \\ \overline{CA}^{N_p} & \bar{C}\left(\sum_{i=0}^{N_p-1} \bar{A}^i\right)\bar{B} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 \end{bmatrix} \tag{13}$$

$$\Gamma = \begin{bmatrix} CB & \cdots & \cdots & 0 \\ CAB & CB & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{N_p-1}B & CA^{N_p-2}B & \cdots & CA^{N_p-N_c}B \end{bmatrix} \tag{14}$$

However, the constraint generally is in amplitude of control input. To deal with it, the equation (15) is used as follows,

$$U_d = DU - E_1 u_{k-1} = DU + GX \tag{15}$$

the matrix forms of U, E_1, D, and G is expressed in [18].

In MPC, control signal U is desired to minimize the cost function (J). In MPC as tracking problem, the cost function is as follows,

$$J = e_{k+N_p}^T \bar{Q} e_{k+N_p} + \sum_{t=0}^{N_p-1}\left(e_{k+t}^T \bar{Q} e_{k+t}\right) + \sum_{t=0}^{N_c-1}\left(\Delta u_{k+t}^T \bar{R} \Delta u_{k+t}\right) \tag{16}$$

with the tracking error $e_k = y_k - \omega_k$, $N_p \leq N_c$, $\bar{Q} = \bar{Q}^T \geq 0$, and $\bar{R} = \bar{R}^T \geq 0$, so in general form up to the N_p prediction horizon and N_c control horizon, equation (16) can be written as follows,

$$J = e_k^T \bar{Q} e_k + E^T Q E + U_d^T R U_d \tag{17}$$

where $E = Y - \Omega$ and $E = \begin{bmatrix} e_{k+1} \\ e_{k+2} \\ \vdots \\ e_{k+N_p} \end{bmatrix}, Y = \begin{bmatrix} y_{k+1} \\ y_{k+2} \\ \vdots \\ y_{k+N_p} \end{bmatrix}, \Omega = \begin{bmatrix} \omega_{k+1} \\ \omega_{k+2} \\ \vdots \\ \omega_{k+N_p} \end{bmatrix}$.

By manipulating the cost function in equation (17) to fit the equation (6), so the following equation is obtained,

$$J = J_x + X^T[\bar{\Phi}^T Q \bar{\Phi} + G^T R G - F_x^T M^{-1} F_x^T]X + (U + M^{-1}F_x X)^T M (U + M^{-1} F_x X) \tag{18}$$

with,

$$J_T = \frac{1}{2}\left(U + M^{-1}F_x X\right)^T M \left(U + M^{-1}F_x X\right) \tag{19}$$

Therefore, the equation (18) changes to,

$$J = J_x + X^T\left[\bar{\phi}^T Q \bar{\phi} + G^T R G - F_x^T M^{-1} F_x^T\right]X + 2J_T \tag{20}$$

From the objective function, it is desired to minimize the J value with respect to the optimal U value where $U_{min} \leq U \leq U_{max}$ is just affected by J_T function. Therefore, to obtain the optimal solution of U, the equation of J_T is derived toward U. The optimal solution of U without constraints is shown in equation (21) below,

$$U = -M^{-1}F_x X = -M^{-1}\begin{bmatrix} F_1 & F_2 & H \end{bmatrix}\begin{bmatrix} x_k \\ u_{k-1} \\ -\Omega \end{bmatrix} \tag{21}$$

with,

$$M = [\Gamma^T Q \Gamma + D^T R D]$$
$$H = \bar{\Gamma}^T Q;\ \bar{\Gamma} = \Gamma D$$
$$F_1 = \bar{\Gamma}^T Q \emptyset_1$$
$$F_2 = \bar{\Gamma}^T Q \emptyset_2 - D^T(\Gamma^T Q \Gamma + R)E_1$$

Hildreth's Quadratic Programming

One of the simple algorithm, called Hildreth's QP, is used to solve dual problem [19]. The main idea of Hildreth's algorithm is by adjusting vector λ_i, which is Lagrange multiplier, to minimize the Lagrangian function of cost function J below,

$$J_l = J_x + X^T\left[\bar{\phi}^T Q \bar{\phi} + G^T R G\right]X + U^T M U + 2U^T F_x X + \lambda_i^T (NU - \gamma) \tag{22}$$

If $\lambda_i < 0$, vector λ_i changes to 0 ($\lambda_i = 0$) or in other words, non-negative value is only available for vector λ_i.

The method of Hildreth's QP can be written as follows,

$$\lambda_i^{m+1} = \max(0, \omega_i^{m+1}) \tag{23}$$

with,

$$\omega_i^{m+1} = -\frac{1}{s_{ii}}[k_i + \sum_{j=1}^{i-1} s_{ij}\lambda_j^{m+1} + \sum_{j=i+1}^{n} s_{ij}\lambda_j^m] \tag{24}$$

where the scalar s_{ij} is the *ij-th* element in the matrix $S = NM^{-1}N^T$, and k_i is the *i-th* element in the vector $K = \gamma + NM^{-1}F_x X$. The equation S and K are obtained by manipulating the lagrange multipliers and Karush-Kuhn-Tucker method. The vector N is constraints vector of $f(x, u, y, \ldots)$ and the scalar γ is maximum and minimum value of constraints.

The working principle of Hildreth's algorithm is shown in Fig. 9 below,

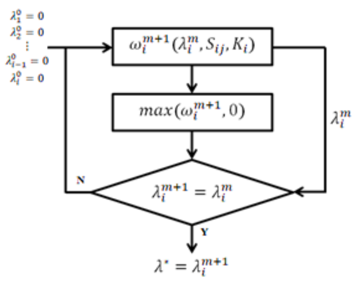

Fig. 9 Block diagram of Hildreth's algorithm [20].

B. Kalman Filter

Kalman filter is an iterative mathematical process that the set of equations and consecutive data inputs are used to estimate the values. Kalman filter basically has 2 step processes as follows,

1. Predict process

$$\hat{x}_k = \overline{A}_k \hat{x}_{k-1} + \overline{B}_k u_{k-1} \tag{25}$$

$$P_k = \overline{A}_k P_{k-1} \overline{A}_k^T + Q_{e_k} \tag{26}$$

In equation (25) and (26), P must remain symmetric and positive definite. Q_e must be symmetric and positive definite or positive semi definite.

2. Update process

$$\hat{x}_k^{'} = \hat{x}_k + K^{'}\left(\vec{z}_k - \overline{C}_k \hat{x}_k\right) \tag{27}$$

$$P_k^{'} = P_k - K^{'} \overline{C}_k P_k \tag{28}$$

$$K^{'} = P_k \overline{C}_k^T \left(\overline{C}_k P_k \overline{C}_k^T + R_{e_k}\right)^{-1} \tag{29}$$

In equation (27), (28), and (29), R_e must be positive definite.

In this research, Kalman filter is used to overcome system disturbance and sensor noise and also to estimate the state that is caused by compensating delay process with Pade Approximation. The block diagram of MPC and Kalman filter is shown in Fig 10 below,

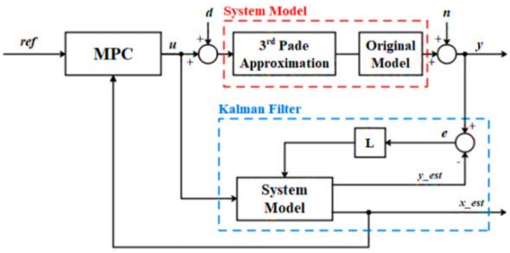

Fig. 10 Control architecture of boiler system

V. EXPERIMENTAL RESULT

In this section, the MPC and Kalman filter responses to control temperature of boiler and to deal with system noise and/or disturbance are provided. The experiment is divided into two scenarios, the first scenario is to evaluate MPC and Kalman filter responses below its boiling point of 30% of alcohol, and the second scenario is to evaluate MPC and Kalman filter responses outside its initial condition. In Fig. 11 below, Kalman filter as an observer and low pass filter is represented.

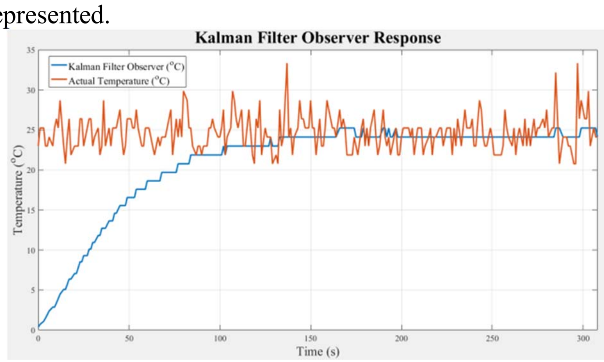

Fig. 11 Responses of Kalman Filter

In Fig. 11 above, it shows that temperature sensor of boiler, pt100, is very noisy but Kalman filter can overcome that problem. Kalman filter can follow the system state in roughly 133 seconds. The parameters of Kalman filter as an estimator being used is shown in Table I below,

TABLE I. Design Parameters of Kalman Filter

Q_e	$10*I_{(6x6)}$
R_e	10

After estimator is designed, the first scenario is implemented to the boiler system. The parameters of MPC being used is shown in Table II below,

TABLE II. Design Parameters of MPC

Prediction Horizon	30
Control Horizon	15
Q_c	$100*I_{(6x6)}$
R_c	0.0001
Constraints	$0 \leq u_k \leq 100$

The prediction horizon being used is obtained by dividing steady time of temperature response, 1800 seconds, and sampling time of controller which is 60 seconds. The simulation result of MPC and Kalman filter is shown in Fig. 12 and Fig. 13 below,

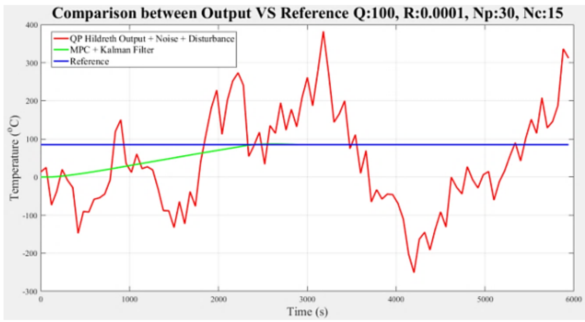

Fig. 12 Simulation of MPC + Kalman Filter

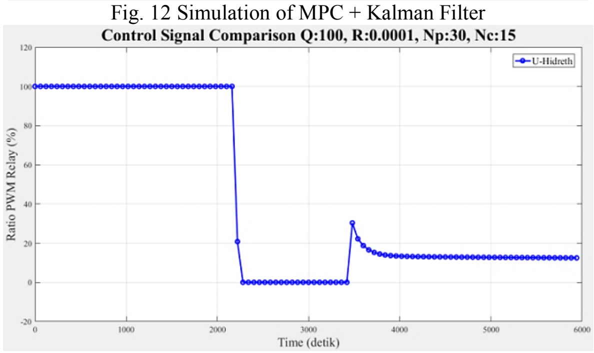

Fig. 13 Control Signal of MPC + Kalman in Simulation

The simulation result in Fig. 12 shows that MPC and Kalman filter can still track the reference although noise and disturbance exists (green line) but the only MPC can not overcome the system disturbance and sensor noise (red line). In Fig. 13, the control signal of MPC is successfully implemented because it's constrained between 0% and 100%. After simulation result is done, the first scenario is implemented to the real system. The result of first scenario is shown in Fig. 14 below,

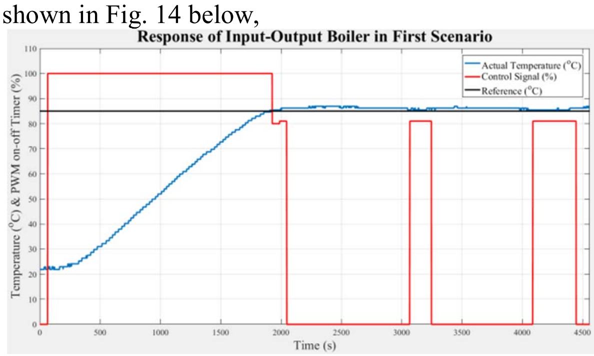

Fig. 14 Input-Output Response of Boiler System in First Scenario

The implementation of MPC and Kalman filter in first scenario shows that boiler can track the temperature reference, 85 ^{o}C, with rise time approximately 2059 seconds and 2.28% overshoot. Even though boiler can track the temperature reference, the temperature offside in steady state condition still exists, that is ± 1.42%.

In second scenario, the reflux state is opened during the process, the reference is changed to 87 ^{o}C, and the constraint is set to $0.1 \leq u_s \leq 100$. The result of second scenario is shown in Fig. 15 below,

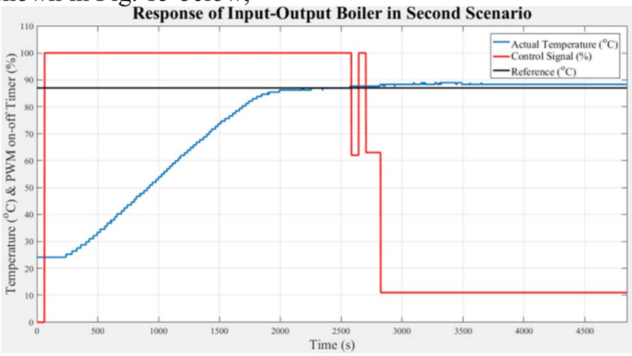

Fig. 15 Input-Output Response of Boiler System in Second Scenario

In Fig. 15 above, MPC and Kalman filter can keep tracking the temperature reference. The rise time is around 2024 seconds, 0% overshoot, and temperature offside in steady state condition is roughly ±1.5%.

IAE (Integral Absolute Error), ISE (Integral Squared Error), ITAE (Integral Time Absolute Error), and ITSE (Integral Time Squared Error) are then analyzed to see the performance of controller and it is shown in Table III below,

TABLE III. IAE, ISE, ITAE, and ITSE of First and Second Scenario

	First Scenario	Second Scenario
IAE	$5.0851*10^4$	$5.666*10^4$
ISE	$2.1922*10^6$	$2.5444*10^6$
ITAE	$3.2658*10^7$	$3.5210*10^7$
ITSE	$7.5899*10^8$	$1.0085*10^9$

The energy optimization of boiler per operation is also calculated to find out the effect of MPC in energy optimization and it is shown in Table IV below,

TABLE IV. Energy Optimization Comparison

	Scenario I	Scenario II	Normal Operation
Energy hours per operation (Wh)	816.729	1078.416	1400

In table IV above, the boiler in scenario I consumes less energy rather than boiler in scenario II or in normal operation. The reason of that is because in scenario II, the lower constrain is set to 0.1% PWM so the boiler consumes more energy.

VI. CONCLUSION

This research succeed in designing and implementing the temperature control of Boiler System with assuming the mass change of mixture as a disturbance system. 2 scenarios are implemented to test the controller outside its initial condition. The experimental result of first scenario shows that boiler needs around 2059 seconds to track the reference with 2.28% overshoot but the steady state offside still exist. In second scenario, the boiler needs 2024 to track the reference without overshoot but the steady state offside still exist. At the end of this research, the IAE, ISE,ITAE, and ITSE is calculated and shows that the controller works well around its initial condition and the controller can still overcome the condition outside its initial condition. MPC can also maintain energy optimization by saving 41.6% in scenario I and 22.97% in scenario II per operation compared to normal operation.

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